Towards A Comprehensive Model Of Window Control Behaviour: A Survey-based Investigation On Interdisciplinary Drivers In Danish Dwellings

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Abstract

Bridging the gap between predicted and real energy consumptions in buildings has become a crucial task in the building energy research community. In this context, numerous studies confirmed occupant behaviour to be a key driver of uncertainty that impacts building energy performance and environmental indoor conditions. In particular, occupant's action of window opening/closing has an important impact on building energy use and indoor environmental quality by changing the amount of fresh air to the building. However, most proposed approaches for modelling window control behaviour consider time-related factors and physical parameters such as indoor or outdoor environmental variables while less attention is paid to other influential factors such as psychological, social and contextual drivers or individual thermal comfort attitudes and preferences of the occupants. The aim of this paper was to model window opening behaviour by combining field measurements with survey-based information of 14 Danish town houses. In particular, in this study, individual thermal comfort attitudes and preferences of the occupants are introduced in a Bayesian network-based modelling process.

Introduction

Nowadays, the building energy research community is aware of the pivotal role of occupant behaviour in contributing to a large share of uncertainty when predicting building energy demand and thermal comfort conditions of the indoor environment (Masoso and Grobler, 2010; Yan et al., 2017; Mahdavi, 2011). To meet individual comfort criteria or other necessities, occupants regulate heating/cooling set points, lighting levels, windows and sunscreens, or other installed HVAC systems and building envelope features. It is not difficult to envision the stochastic nature of the human-building interaction, since individuals might perceive the indoor environment in different ways, or have different preferences, priorities, habits or different constraints (e.g. social or economic) when regulating the indoor environment. Indeed, existing field studies have demonstrated that buildings with a similar layout and same climatic conditions are characterised by large discrepancies between building energy demands (Andersen et al., 2007; Clevenger et al., 2014).

Among possible human-building interactions, window control behaviour has an important impact on building energy use and indoor environmental quality by changing the amount of fresh air to the building. Several researchers proposed stochastic models for predicting the occupant’s window control behaviour (Rijal et al., 2008; Haldi and Robinson, 2009; Schweiker et al., 2012; Zhang and Barrett, 2012; Andersen et al., 2013; Andersen et al., 2016; Shi and Zhao, 2016; Jeong et al., 2016; Jones et al., 2017). Typically, the proposed models are based on statistical algorithms to predict the probability of a specific condition or event, such as the window state or the window opening/closing action, given a set of environmental or other influential factors (Borgeson and Brager, 2008). Most popularly used methods include logit analysis (Nicol, 2001; Andersen et al., 2013), probit analysis (Zhang and Barrett, 2012), and Markov chain processes (Haldi and Robinson, 2008). Some approaches identified temperature to be the most important driver (Warren and Parkins, 1984; Rijal et al., 2008) although there is no consensus about whether indoor or outdoor temperature is dominant in determining the behaviour. In the residential sector, most models based on datasets including CO₂ concentration find CO₂ to be a dominant driver (Andersen et al., 2013; Cali et al., 2016). Further studies identified time-related factors (e.g. time of the day, season, current window state) as key variables to predict window control actions (Pfafferott and Herkel, 2007; Haldi and Robinson, 2008; Yun and Steemers, 2008).

However, much is still unknown about occupant behaviour and further exploration is required to gain a deeper knowledge on a comprehensive set of motivations that drive the occupants to perform a certain action. Several studies highlight that, next to physical and time-related factors, it is necessary to take into account “individual” factors of occupants, such as the personal background, energy-related attitudes, perception or personal preferences related to the indoor environment (Schweiker, 2017; Fabi et al., 2012). Wei et al. (2014) identified 27 drivers that have been evaluated in previous behavioural studies and showed that at present, none of them can be identified confidently as having no influence. Next to physical and time-related drivers, the authors list occupant age, gender, culture/race, educational level, social grade, household size, family income, thermal sensation, perceived IAQ and noise, health, heating price, and energy use awareness as potential driving factors.

The objective of this paper was to gain a deeper knowledge on human interactions with windows, with
particular regard to individual thermal comfort attitudes and preferences next to environmental variables. We combined field measurements with survey-based information of individual household members collected in 14 Danish town houses. Based on the collected dataset, the Bayesian Network (BN) framework was applied to capture underlying relationships between these factors and window control actions.

**Methodology**

**Bayesian Network framework**

BNs are graphical models that represent a set of variables and their conditional dependencies via a Directed Acyclic Graph (DAG). Hence, BNs consist of two parts: a graphical model and an underlying conditional probability distribution. In detail, nodes represent the variables \( X_1, X_2, \ldots, X_n \), and the dependencies between variables are depicted as directional links corresponding to conditional probabilities. The Markov property of the BNs implies that all the probabilistic dependencies are graphically shown via arcs and that child nodes only depend on the parent nodes (Korb and Nicholson, 2003). The joint probability distributions for a discrete case (Equation 1) and a continuous case (Equation 2), are defined as follows:

\[
P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|\text{Parents}(X_i)). \tag{1}
\]

\[
f(X_1, \ldots, X_n) = \prod_{i=1}^{n} f(X_i|\text{Parents}(X_i)). \tag{2}
\]

*Figure 1: Example of a BN.*

The probabilistic dependencies among the variables can be evaluated with the arc strengths between nodes. The arc strength measures the importance of individual parent nodes on predicting the state of their child node. The strength is measured by the score gain or loss as the result of removing one arc while keeping the rest of the network fixed. Negative strength values indicate decreases in the network score due to the arc’s removal, and positive values indicate increases in the network score. A low arc strength indicates a strong relationship between the two variables linked by the arc. The A BN-based approach allows for flexibly modelling complex relationships between diverse explanatory variables and window control behaviour by constructing a joint probability distribution over the domain variables through a graphical representation of the model structure (Korb and Nicholson, 2003). BN model allows for structuring a variety of explanatory variables and multiple target variables in a hierarchical manner. Also, BNs are demonstrated to yield good prediction accuracy even with small datasets (Myllymäki et al., 2002). In a previous paper (Barthelmes et al., 2017), the authors explored the applicability of the BN framework for modelling window control behaviour with environmental and time-related factors as key drivers. The validation of the BN model confirmed a high predictive power of the model and its successful application for modelling window control behaviour. This study also acknowledged some limitations and challenges when modelling with Bayesian Networks. The capability of treating mixed data is crucial for modelling window control behaviour, since the action layer is binary and explanatory variables are often continuous (e.g. indoor environmental variables).

Currently, most available statistical analysis packages and software support either discrete or continuous variables. In this paper, the BN was modelled with the R bnlearn package (Scutari, 2010), which offers some flexibility to model a mix of discrete and continuous variables since it supports the dependence of continuous variables on discrete variables but not the other way around. Hence, it is possible to build a bottom-up model in which the arcs are reversely connected from the discrete target variable to the continuous response variables.

**Field measurements**

In this paper, we analysed field measurements taken in 14 naturally-ventilated apartments located in a same neighbourhood close to Copenhagen, Denmark. Table 1 summarises measurements related to the indoor and outdoor environment conditions, occupants’ interaction with the windows in the living room, and time-related factors. A time resolution of 15-min intervals was used for the analysis, which considers measurements for one month during the heating season (November 2017). The outdoor environmental measurements were acquired from a sensor located in a representative area for the neighbourhood. For the choice of explanatory and target variables the authors refer the reader to (Henriksen and Olsen 2018).

*Table 1: Measured target and explanatory variables.*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Abbreviation</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Indoor environment</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Air temperature</td>
<td>( T_m )</td>
<td>°C</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>( RH_m )</td>
<td>%</td>
</tr>
<tr>
<td>( CO_2 ) concentration</td>
<td>( CO_2_{in} )</td>
<td>ppm</td>
</tr>
<tr>
<td><strong>Outdoor environment</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor temperature</td>
<td>( T_{out} )</td>
<td>°C</td>
</tr>
<tr>
<td><strong>Time-related</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time of the day</td>
<td>Hour</td>
<td>h</td>
</tr>
<tr>
<td><strong>Target</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Window opening action</td>
<td>WOA</td>
<td>0/1</td>
</tr>
</tbody>
</table>

**Survey framework**

To introduce individual characteristics of the occupants or households in the modelling process, we developed a tailored survey framework (Barthelmes et al., 2018). The survey-based information was collected once during the
heating period and was aimed at investigating a more extensive set of potential drivers:

- individual comfort attitudes and preferences;
- physiological factors and individual characteristics (e.g. gender, age, height, weight, smoking habits);
- social and economic factors (e.g. education, household composition, household income);
- perceived control and psychological factors (e.g. satisfaction of control options, knowledge of control options, interaction frequency with controls, safety);
- motivations and habits related to window control behaviour;
- adaptive opportunities (e.g. sequence of actions that occupants perform when they feel hot/cold).

In particular, in this paper we explored the relationship between individual thermal comfort attitudes as well as individual preferences and window control behaviour, since these factors showed a great inhomogeneity among the occupants.

**Individual thermal comfort attitudes**

In the survey, the respondents were requested to indicate their perception of the thermal environment and other factors that influence their thermal sensation (clothing, activity level, perception of drafts). The perception was indicated on a continuous seven-point scale (Figure 2), similar to the Predicted Mean Vote (PMV) thermal scale (Cen, 2007). This subjective data was analysed together with field measurements taken during the compilation of the survey in order to establish the thermal comfort attitudes of the occupants according to the procedure depicted in Figure 3.

The influencing factors on the PMV according to EN15251 standard include environmental factors (air temperature, mean radiant temperature, air speed and humidity) and occupant-related factors (metabolic rate and clothing level). Since mean radiant temperature was not measured in the case studies, it was assumed equal to the indoor air temperature. Also air speed was not directly measured in the case studies, but was assumed based on survey answers. If respondents perceived air movement around them, the air speed was set to 0.2 m/s, in other cases without perceived drafts, the air speed was set to 0.1 m/s.

To take into account individual perceptions of the thermal environment of different occupants, we introduced thermal comfort attitudes (TCAs) that were defined as the numerical difference between the calculated PMV values and thermal sensation vote provided by the individual respondents under the same environmental conditions. Hence, if the TCA < 0, then respondents felt colder with respect to the sensation vote calculated according to EN15251; on the other hand, if TCA > 0, then respondents felt warmer than the sensation vote calculated according to the same standard. Figure 4 summarises the calculated TCA values for the respondents at the moment of the compilation of the survey. We assumed these values to be constant throughout the analyses. In case of 2-person households, the average value of TCAs was considered.

![Figure 2: Survey-based investigation of factors influencing the thermal sensation of the occupants.](image1)

![Figure 3: Definition of Thermal Comfort Attitudes (TCAs), where v=air speed, MET=metabolic rate, lcl=clothing insulation, MRT=mean radiant temperature, T=air temperature, RH=relative humidity.](image2)
Individual preferences

The individual preferences of occupants were elicited by asking them how much they agreed or disagreed with comparative statements. In particular, the aim was to identify preferences in terms of thermal comfort (TC), indoor air quality (IAQ) and energy savings (SAV). For this analysis, we considered the responses to the following statements related to window control behaviour (originally in Danish language):

- **Statement 1 (TC-IAQ):** "When it is cold outside, I would rather feel a little cold to get some fresh air";
- **Statement 2 (TC-SAV):** "I would rather feel a little cold in order to save on the heating bill";
- **Statement 3 (IAQ-SAV):** "I can accept a slightly bad indoor air quality in order to save the heating bill".

The respondents could indicate their opinion around these statements on a continuous 5-point scale (from "I strongly disagree" to "I strongly agree"). As shown in Figure 5, 70% of the respondents preferred to have good indoor air quality and feel a little bit cold, while the priority of 17% of the respondents was to have adequate thermal comfort conditions. At least 87% of the respondents preferred to have a pleasant thermal environment and an adequate indoor air quality, rather than saving on the heating bill (Figure 6 and 7).

Based on these outcomes, the preference of each occupant (PREF) can assume three states: TC (respondent’s priority is thermal comfort), IAQ (respondent’s priority is indoor air quality), and SAV (respondent’s priority is saving on heating bill). The state of PREF was defined by:

- **PREF=IAQ** if S1 was in agreement and S3 was in disagreement;
- **PREF=TC** if S1 and S2 were in disagreement;
- **PREF=SAV** if S2 and S3 were in agreement;

where Sn is the number of the statement.

This procedure allowed classifying the households according to their preferences. In particular, 71% of the households were classified as PREF=IAQ, 22% as PREF=TC, and only 7% as PREF=SAV.

Results

This section proposes the results of the BN modelling procedure that investigated relationships between window opening behaviour and (i) a set of “common” environmental and time-related drivers (indoor temperature, relative humidity, and CO₂ concentration, outdoor temperature, time of the day), and (ii) individual characteristics of the occupants in terms of thermal comfort attitude and preferences. Figure 8 depicts the naïve (only one class node) bottom-up model that allows for treating mixed data in the same network and avoiding loss of information that usually occurs when discretizing continuous variables. Table 1 summarises the arc strengths between the target and explanatory variables. This analysis showed that the strongest probabilistic
dependencies were found between window opening actions and preferences, thermal comfort attitude, indoor relative humidity, and indoor CO$_2$ concentration. The strong relationship between window opening behaviour and relative humidity might be explained by cooking activities in open-plan living rooms.

Figure 8: Bottom-up BN model for modelling window opening actions (WOA) – green dots refer to field measurements while blue points refer to survey-based investigation.

Table 1: Arc strengths.

<table>
<thead>
<tr>
<th>N°arc</th>
<th>from</th>
<th>to</th>
<th>arc strength</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>WOA</td>
<td>PREF</td>
<td>-151.90</td>
</tr>
<tr>
<td>2</td>
<td>WOA</td>
<td>TCA</td>
<td>-125.63</td>
</tr>
<tr>
<td>3</td>
<td>WOA</td>
<td>RHin</td>
<td>-99.56</td>
</tr>
<tr>
<td>4</td>
<td>WOA</td>
<td>CO2in</td>
<td>-95.55</td>
</tr>
<tr>
<td>5</td>
<td>WOA</td>
<td>Hour</td>
<td>-18.62</td>
</tr>
<tr>
<td>6</td>
<td>WOA</td>
<td>Tout</td>
<td>-4.63</td>
</tr>
<tr>
<td>7</td>
<td>WOA</td>
<td>Tin</td>
<td>-1.24</td>
</tr>
</tbody>
</table>

The BN model was inferred to define probabilities of a window opening action given the single explanatory variables. The outcomes of the queries can be summarised as follows:

- **Environmental variables**: in line with existing literature, the results indicate that the probability of opening a window increases in correspondence of a higher CO$_2$ concentration (Figure 9b), indoor air temperature (Figure 9c), and outdoor air temperature (Figure 9d);
- **Time-related factors**: the probability of opening a window increased from the early morning hours to noon, and then decreased again until the late evening hours (Figure 10);
- **Preferences**: the results show that the probability of opening a window is very reduced in households that were classified with a “TC” preference, or rather the priority to maintain adequate thermal comfort conditions (Figure 11);
- **Thermal comfort attitudes**: interestingly, the outcomes of this analysis clearly shows that the probability of a window opening action increases with higher thermal comfort attitude values. This means that the window is more likely to be opened if during the compilation of the survey, the respondents indicated higher thermal sensation votes (felt warmer) with respect to the ones calculated according to Standard EN15251.
Figure 9: Probability of opening a window given (a) indoor relative humidity, (b) CO$_2$ concentration, (c) indoor air temperature, and (d) outdoor air temperature.

Figure 10: Probability of opening a window (WOA) given the time of the day.

Figure 11: Probability of opening a window (WOA) given preferences in terms of indoor air quality (IAQ), thermal comfort (TC), and energy cost savings (SAV).

Figure 12: Probability of opening a window (WOA) given the Thermal Comfort Attitude (TCA).

**Discussion**

In this paper, we proposed a naïve Bayesian network (only one class node) to capture probabilistic dependencies among environmental, time-related and individual drivers that influence window control behaviour. In order to fully exploit the capabilities of the Bayesian Network approach, it is possible to further extend the model to explore (i) other interdisciplinary drivers (e.g. social or economic factors), (ii) other control actions (e.g. thermostat control, window blinds adjustment, light switching), or (iii) the capability of the network to structure influencing factors in a hierarchical manner. As an example, we found that in this case study the thermal comfort attitude (TCA) was linked to individual physiological characteristics of the respondents, such as age, weight, and height. This was done by developing a Bayesian Network as shown in Figure 13. The probabilistic queries of this BN model are shown in Figure 14 and investigated the probability that the respondents’ thermal comfort attitude was less than 0, or rather the probability of feeling colder with respect to values calculated with Standard EN15251. The respondents felt colder than the calculated PMV values with increasing age (Figure 14a), lower weight (Figure 14b), and lower height (Figure 14c). No significant differences were found for the gender. Further work will include the exploration of “sub-networks” that can be integrated in the existing network to create one extensive and hierarchical model.

Figure 13: BN model for exploring probabilistic dependencies between TCA (target) and physiological characteristics of the occupants.
Indeed, Bayesian networks, in principle, allow for modelling complex hierarchical relationships between a large number of continuous and discrete variables through a clear semantic graphical representation. The graphical representation is a valuable benefit since the structure and its underlying probabilistic dimension are easily interpretable for modellers in the building simulation community. However, whether current modelling environments (e.g. R bnlearn) are able to suitably develop a hierarchical model for window control behaviour needs to be carefully addressed, since they have limited capabilities to handle the mixed dataset only when continuous variables depend on discrete variables.

As regard the data collection, in practice, it is challenging to collect survey-based information with the same time steps as field measurements. In this case study, we collected survey-based information once during the heating period, while field measurements were collected in increments of minutes during a full year. It was therefore necessary to assume survey responses (e.g. comfort attitudes, preferences) constant during time.

**Conclusion**

This paper proposed a BN-based modelling procedure for window control behaviour that included not only environmental and time-related factors, but also a preliminary set of individual characteristics of the respondents, such as thermal comfort attitude and preferences. The study was based on a combination of field measurement and survey-based investigations in 14 Danish town houses. In this case study, the outcomes revealed significant probabilistic dependencies between individual thermal comfort attitudes and window control behaviour.

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**References**


